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REVIEW

Exploring the Intersection of Artificial Intelligence and Microgrids in Developing Economies: A Review of Practical Applications

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Abstract

Purpose of Review This paper reviews practical challenges for microgrid electrification projects in low- and middle-income economies, proposing a Social-Technical-Economic-Political (STEP) framework. With our STEP framework, we review recent Artificial Intelligence (AI) methods capable of accelerating microgrid adoption in developing economies.

Recent Findings Many authors have employed novel AI methods in microgrid applications including to support energy management systems, fault detection, generation sizing, and load forecasting. Despite these research initiatives, limited works have investigated the specific challenges for developing economies. That is, high-income countries often have high-quality power, reliable wireless communication infrastructure, and greater access to equipment and technical skills. Accordingly, there are numerous opportunities for the adaptation of AI methods to meet the constraints of developing economies.

Summary In this paper, we provide a comprehensive review of the electrification challenges in developing economies alongside an assessment of novel AI approaches for microgrid applications. We also identify emerging opportunities for AI research in the context of developing economies and our proposed STEP framework.

Keywords Microgrids · Artificial intelligence · Electrification · Developing economies

Introduction

Affordable and high-quality electricity is essential for the advancement of modern economies. Developing economies, especially those with large rural populations, face significant challenges in achieving sustainable economic and social development due to inadequate electricity access [1]. According to the International Energy Agency, around 775 million people worldwide lack access to electricity, while 75 million more may lose access due to energy affordability [2]. Africa accounts for nearly 600 million of those without electricity, with the majority of the remaining population residing in regions of Asia.

Considering the ongoing climate crisis, there is an immediate need to shift to low-carbon or carbon-free energy systems. The Intergovernmental Panel on Climate Change indicates that renewable energy must account for 70 to 85% of total electricity by 2050 [3]. Developing economies are expected to account for a crucial portion of the energy transition as their electrical demands are expected to grow at 3% per year until 2040, compared to a 0.9% growth rate in high-income countries [4, 5]. The urgent call for action presents a unique opportunity for un-electrified regions in Africa and Asia to adopt a renewable and restructured energy approach. With the implementation of appropriate policies, social initiatives, and investments, renewable energy can enhance electrification in developing economies.

Building on the potential of renewable energy, Artificial Intelligence (AI) has gathered much interest in the energy

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community as it provides advanced data analysis and insight opportunities. Significant research efforts have been made with AI and power systems; however, limited research efforts have focused on AI's impact on microgrids in low- and middle-income countries. As such, the majority of power systems AI research often perform analysis using models built using ideal electrical sensing, substantial consumer loads, and high economic accessibility, assumptions that are often unrealistic in developing economies. Previous reviews in the literature have focused on each of these challenges separately, with comprehensive reviews of the social [6], technical [7••], economic [8], and political challenges [9], in addition to the general state of energy in developing regions [10–13]. Likewise, reviews of AI research on microgrids have been well documented, focusing on the areas of energy management systems [14], fault response resilience [15], load forecasting [16], and general AI algorithms applications [17•, 18•] alongside many others.

This paper aims to holistically examine AI solutions and their integration within emerging economies, bridging the gap between academic scholarship and real-world contexts. To our knowledge, this paper represents the first such type of review with the analysis of AI applications in microgrids with a specific focus on the limitations inherent in low- and middle-income countries. The chief objectives of this review are

1. To provide insights into the *s*ocial, *t*echnical, *e*conomic, and *p*olitical (STEP) rural electrification challenges unique to developing economies,
2. To review the application of AI in the context of microgrids in developing economies, and
3. To propose future research directions and potential AI advancements in microgrids located in low- and middle-income countries.

This paper is structured as follows. In Section Background, we present important background knowledge on electrification in developing economies. In Section Challenges Facing Electrification in Developing Economies, we present the *s*ocial, *t*echnical, *e*conomic, and *p*olitical (STEP) model for evaluating and integrating new electrification methods. Section A Review of AI Applied to Microgrids in Developing Economies provides an overview of existing microgrid AI algorithms and includes suggestions for how to adapt these algorithms to include the constraints of a developing economy. Section Future Artificial Intelligence Research provides future opportunities for AI research to benefit the constraints of low-income countries. This work draws on academic literature as well as an ongoing case study of electrification in Kenya and Uganda and seeks to merge the discrete threads of AI advancements and microgrid development.

Background

Access to electricity has been associated with numerous developmental and welfare benefits, such as increased economic opportunities, better quality of life, improved health, and greater educational attainment [20–22]. Renewable energy electrification in regions without electricity can yield additional social benefits. Electrification could introduce awareness and opportunities for refrigeration, proper lighting, and electrical based clean cooking, which can all improve the quality of life [23–25].

As a testament to the state of energy in developing economies, Fig. 1 depicts the electrification rates in Africa by country, with darker colors indicating higher rates of electrification [19]. As shown, many countries have electrification rates below 50%, with the electrification rate in South Sudan as low as 7.2% [19]. The limited access to electricity in these regions highlights the opportunities for alternative technical solutions. While electricity adoption is a widely used metric, it does not take into account the quality of electricity and population distribution—which are also extremely important in bolstering widespread adoption of electricity [1]. In fully electrified countries like South Africa, load shedding and frequent power quality issues have resulted in a reduced reliance on electrical appliances, limiting further electricity adoption [26–28].

In efforts to improve both reliability and electricity access, microgrids are often suggested as an innovative and cost-effective solution [29]. A microgrid is a localized grouping of electricity generators and electrical loads capable of operating independently of the centralized grid. Depending upon the connection with the main grid structure, microgrids can take on two forms—grid-connected or islanded (standalone) [30].

A *grid-connected microgrid* aims to enhance reliability, reduce transmission demands, and provide an alternative power source during instances of large-scale outages by disconnecting autonomously from the main grid structure. On the other end of the spectrum is the *islanded microgrid*, which are self-sustaining, standalone entities supplying electricity without any connection to the main grid. Islanded microgrids are especially relevant in the context of rural electrification of regions already devoid of grid power.

With the aim of achieving universal energy access by the year 2030, solar-based microgrids have received significant interest from governments and organizations worldwide, with the United Nations suggesting their implementation as an important part of achieving the Sustainable Development Goal 7 [13]. Recent reports by the International Energy Agency have supported this agenda with estimations that more than 490 million individuals are expected to benefit from over 217,000 microgrids by 2030 [31]. With the ambitious goals set forth by international organizations and

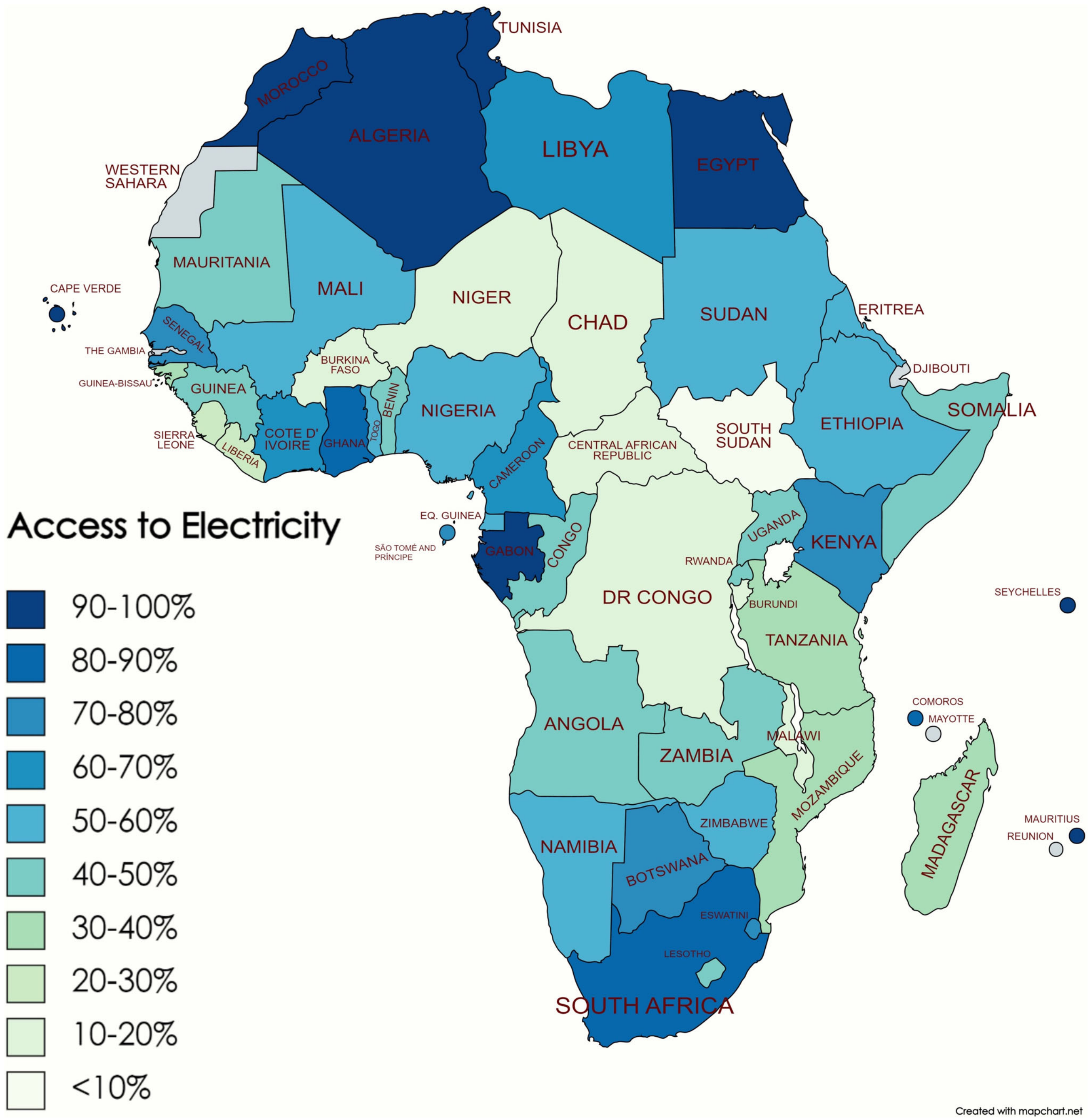

Fig. 1 Access to electricity in African countries as a percentage of the total population [19]

governments worldwide, understanding the social, technical, economic, and political barriers in developing economies is paramount to effective microgrid implementation.

Challenges Facing Electrification in Developing Economies

The drive to extend electricity services to rural regions in developing economies has been a longstanding initiative by the UN, the World Bank, non-profit organizations, and governments worldwide [13, 19, 32]. Despite the significant interest in electrification, electrification rates have progressed slowly, with many projects failing due to social, technical, economic, or political challenges that were not adequately addressed [33, 34].

In this section, we examine and identify four key pillars reflecting challenges in developing economies. It is important to keep in mind that these pillars are often heavily codependent and can be segmented into a variety of subsequent challenges. The categories, as represented in Fig. 2, are *s*ocial, *t*echnical, *e*conomic, and *p*olitical (STEP). Through an understanding of the STEP challenges, we provide a foundation for identifying and implementing effective strategies for accelerating electricity access in remote regions.

Social Challenges

The success of an electrification project often hinges on the involvement of all stakeholders from the outset—from local communities to developers and governmental organizations [7••, 35]. Cultural and behavioral differences oftentimes serve as barriers to electrification as they may incur significant societal and cultural change [36].

In communities that are first exposed to regular electricity access, proper education is crucial to achieving a successful transition. Many households in low-income communities face misconceptions related to energy benefits, electrical safety, and usefulness of electrical equipment [37]. A lack of understanding around which appliances use high amounts of electricity and a misunderstanding of electrical best practices challenge adoption as well. Due to economic constraints, rural households frequently employ inefficient appliances—further increasing their electrical demand and their impact on the planet [38]. Misconceptions about renewable energy sources are common as well, with household solar battery systems seeing short lives due to pervasive overdischarge of battery systems, leading to premature degradation [39].

Contrary to the general optimism around renewable energy's role in facilitating electricity accessibility, awareness lags significantly. For example, in Nigeria, nearly 40% of the population is unaware of the potential for solar photovoltaic systems [40]. Focusing on grassroots-level education, targeting women (often traditionally in charge of household energy management) can enable a smoother transition to modern energy systems [41].

Oftentimes, an energy system will be set up for a community by an external organization and donated to a rural community afterward. A lack of clear understanding and funding post installation often leads to short-lived systems with unclear expectations on who will be responsible for management [42]. In remote communities, system maintenance and responsibility are further complicated by a lack of skilled and qualified technicians [43]. Remote sites may confront high costs and long lead times in obtaining replacement parts, which might not be locally available [44]. The long-term sustainability of microgrids relies heavily on local skills and supply chains. Despite skills development, trained technicians might be swayed to migrate to urban areas for better pay. Therefore, overcoming reliability challenges in rural microgrids requires proper training and retention of local operators and technicians [45].

Political Challenges

The energy sector is particularly susceptible to corruption due to its capital-intensive nature, high degree of public-private coordination, and large amounts of public procurement [46]. While the visibility of such corrupt practices is often particularly pronounced in regions of Sub-Saharan Africa, it is imperative to acknowledge that personal and financial gains often supersede public interest in countries worldwide. Various forms of corruption may persist throughout the lifecycle of an energy project, including *rent-seeking*, which entails the extraction of excess value from an investment not

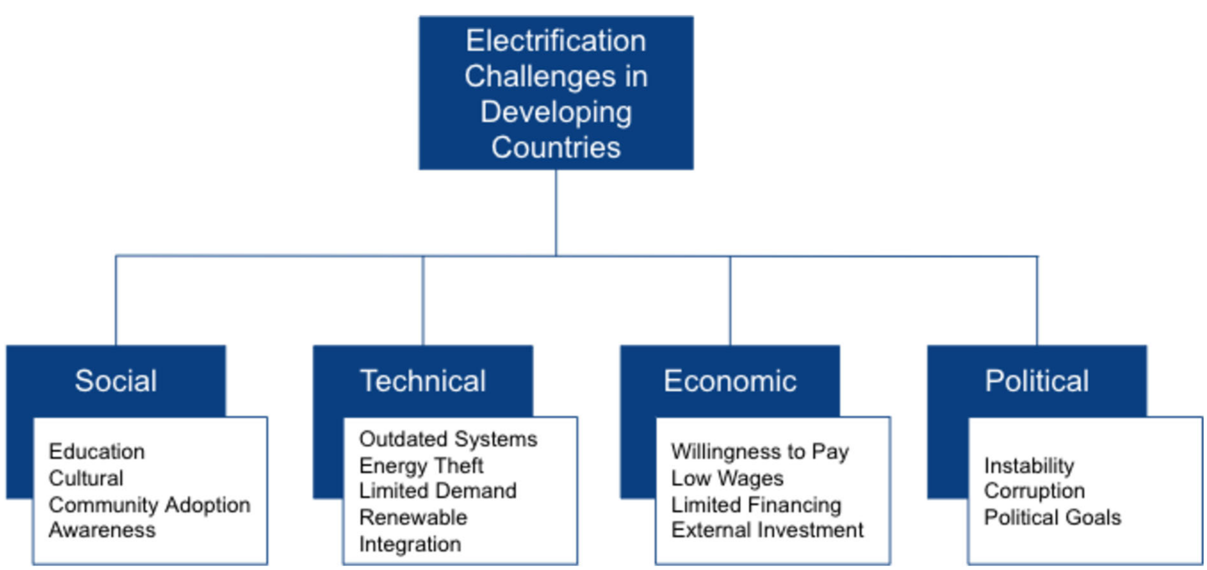

Fig. 2 Mapping the challenges for electrification in developing economies: interplay of social, technical, economic, and political elements

fully owned by the entity or official. *Patrimonialism* involves transferring value to unrelated insiders to maintain political patronage, and *reallocation of ownership* occurs when power actors gain control over energy systems during planning and construction phases, at the cost of initial investors [47–49]. At the energy service delivery stage, which encompasses new electrical connections, meter arrangements, and billing, corruption can inflate costs, spur uncertainty, and deter investment, which can have a detrimental impact on social stability and economic development [14, 50]. Public sector corruption is also unfortunately existent; a case study in Nigeria showed roughly $16 billion USD allocated for power sector renovations between 1999 and 2007 was squandered through corruption and poorly managed bureaucracy [51]. Private sector corruption is just as prevalent, involving manipulations and bribes to influence political decisions and bypass environmental guidelines, an area which has been exploited through many examples in the USA and Australia [52, 53].

Interestingly, despite being traditionally associated with the fossil fuel industry, forms of corruption have migrated to the realm of renewable energy as well [50]. Subsidized renewable energy schemes are becoming avenues for rent-seeking, leading to problems often ignored due to the sector's relative novelty [54, 55]. An example of these areas of corruption, as presented by community members from a month-and-a-half field survey in Africa, are some models that corruption impacts energy projects and day-to-day life.

Model 1: Large Scale Contracts Organization A secures significant funding, potentially government or externally sourced, for the execution of an energy solution. The responsibility falls on Organization A to appoint subcontractors for the execution of the project. In lieu of awarding contracts to the most fitting companies, preferential treatment is often extended to close acquaintances or those who suggest a financial gain to the part of Organization A in charge of contract assignments. In turn, companies that are operating in the best interest of the people may be neglected unless they can promise some economic or political advantage or tie.

Model 2: Inter-Contract The second model entails Organization B receiving a contract from Organization A for connecting a specific number of people to the power grid. Organization B provides an accurate quote to Organization A for the installment cost but installs at half of what was expected or with cheaper components. The leftover hardware is then resold to other contractors or, in some cases, back to Organization B. This can lead to early equipment failure, potentially harmful conditions, and often, the requirement for the work to be redone.

Model 3: Low-Level Corruption The third type of corruption, recognized as the most prevalent by community members, can best be illustrated through unequal power quality. In this situation, political leaders or people with economic influence receive higher quality electricity, with any power disturbance being attended to promptly. In some situations, service companies accept bribes and favors as a way to ensure that power remains reliable to the person in power.

Economic Challenges

Microgrid-based rural electrification is often met with an array of economic hurdles. In rural and remote areas, a large portion of the community often depends on substance farming and other forms of infrequent or unofficial income, with the average income often falling below $2 USD per day [56–58]. The limited access to capital makes affording electricity-intensive appliances such as electric stoves, refrigerators, and electric water pumps very difficult. One solution considering the limited capacity for capital expenditure for community members is a microfinance-based approach, where money can be borrowed for a small-scale investment [59]. Unfortunately, many microfinance companies in Africa have faced challenges with long returns on investments, high default rates, and income instability [60–63]. Persistent issues such as the quality of power supply and infrastructure robustness compound the risk for prospective private sector investors [64, 65].

When funding and policy do arrive, microfinance-based plans are frequently plagued by political instability and socio-economic complications specific to some developing economies [66]. The challenge is highlighted by a recent development in Kenya, which has been the recipient of large efforts to extend the grid to their rural customers, seeing a 30% increase in the number of electrified households from 2013 to 2018 [67]. A key assumption behind the electrification initiative was the well-documented correlation that economies in low-income countries increased proportionately due to electrification rates [68]. However, electricity-based economic stimulation has been recently put to the test in Kenya as economic rates in rural communities have not increased as much as anticipated post-electrification. As a result, customers have exhibited revenues below expected, and Kenya Power is now faced with the challenges of maintaining an overly spread out grid with less financial resources than expected [69, 70].

Public sector and donor applications have often facilitated great strides in electrification, but they do not come without their problems. Political interests and inefficiency often burden public sector electrification [71], while donor efforts are limited to available funding and have often been challenged with providing consistent long-term plans and funding [8]. Private sector investment has been suggested as a potential solution to donor and public sector challenges. However, investment decisions hinge primarily on balancing risks and anticipated rewards. When discussing investment into a microgrid, the private sector often bring up concerns of both high risk and low return on investment [72]. Another prevalent challenge stems from the electricity price regulations in various countries and jurisdictions. Many countries set a maximum price of electricity while requiring a certain standard of electricity reliability to be met, making it increasingly difficult for the private sector to achieve dependable returns [60, 73]. Financing such microgrid projects relies heavily on secure revenue streams to cover operating costs, debt repayment, and ensuring a return to the equity investors [60].

Technical Challenges

Technical hurdles in low-income regions can vary greatly by community size and location and are often impacted by intertwined socio-political and economic challenges. A critical technical obstacle in electrifying Africa, for instance, lies in power quality enhancement. As an example, some microgrids established for health clinics in the Democratic Republic of Congo have exhibited steady-state voltage levels of up to 150% of the nominal [64]. Several other health clinics consistently experience steady-state voltages below 10% of nominal for 6 or more hours daily. Such sustained over-voltage and under-voltage conditions, or otherwise low power quality conditions, result in a significant economic and social impact. Specifically, low levels of power quality are the primary cause of over 70% of medical equipment failures in developing economies [65].

Unexpected community or electrical load growth can lead to improper electricity installation, which further increases faults and decreases safety and reliability. Figure 3 portrays an example of an overcrowded electricity pole with a lone service worker fixing a frequent power outage in Kampala, Uganda. Electrical crowding is further worsened by a lack of accurate electrical sensing, which can make fault and anomaly detection a challenge [26]. Additionally, electricity and equipment theft are also prevalent, which can cause faults, hazardous environments, and inaccuracies in power flow estimation and demand metrics if sensing is present [74].

Additionally, islanded microgrids tend to be more sensitive to variability in energy consumption patterns than grid-tied microgrids due to their smaller geographical size [75]. The high uncertainty in demand, often coupled with a substantial amount of infrequent renewable energy sources, makes microgrid management more challenging. Additionally, load variability further complicates the sizing of the generation system that seeks a minimization of cost while maintaining adequate service quality [76]. Indeterminate load profiles and inefficient second-hand appliances add to the issue, making it challenging to size distributed energy generators according to demand. Technical challenges, such as those previously discussed, offer great opportunities for Artificial Intelligence research to rapidly improve the reliability and adoption of microgrids in developing economies.

A Review of AI Applied to Microgrids in Developing Economies

Artificial Intelligence research has made significant advancements in addressing key technical challenges of microgrid control and operation, including energy demand-side management, security and stability assessment, power system resilience, energy management, and demand response, alongside many more [17•]. In this section, we conduct a comprehensive examination of several of the prevailing technical challenges faced by microgrids in developing economies. Specifically, we examine AI research in the following subcategories: fault detection, sizing, and energy management systems. Table 1 is organized as a comprehensive view of current AI microgrid research, the technology used, and suggestions for expanding further into developing economies.

Energy Management Systems

An energy management system (EMS) is the system responsible for the distribution of available generation to meet the energy load in a microgrid [92]. The primary objective of an EMS is to facilitate the efficient administration of all dispersed energy resources and loads, and it presides over decisions to disconnect from the main grid in grid-connected microgrids. Recently, AI has emerged as a solution to address the multitude of energy management challenges experienced by a microgrid [14].

In rural regions in low-income countries, islanded microgrids are often the most cost effective solution as these areas often do not have access to the main grid [100]. Likewise, these areas do not have readily available access to the internet, and many data monitoring solutions rely on cellular communication over 2 G and 3 G networks. The limited access to reliable internet access furthers the constraint that EMS algorithms must be locally deployable or use extreme data-conscious sensing. In operation in a rural microgrid, an EMS plays a key role in controlling and optimizing functional areas like battery charging, diesel generator operation, and PV resources. The battery storage system is often the most important element of a microgrid and is used to maintain peak load demand via instructions from the energy management system (Fig. 4).

Recent AI advancements employing the use of artificial neural networks [93], fuzzy logic systems [94], and sliding mode controller [95] have shown substantial advantages in managing the uncertainty of renewable energy sources and consumer loads. Complementing these, multi-agent systems, game theory, and Markov decision processes have proven to

Fig. 3 An electricity service worker fixing a frequent power outage due to overcrowding of electricity wires in Kampala, Uganda

be proficient tools for the problems of EMS optimization [17•]. Multi-agent systems foster decentralized decision-making, facilitating cooperative control among microgrid components [98], which increases device autonomy and real-time decision-making flexibility. Meanwhile, game theory applications encourage fairness in energy distribution by dealing with competition among players in a microgrid [101]. Markov decision processes assist in making informed decisions about power generation and allocation in the face of uncertainties in renewable energy sources and loads [99]. These AI techniques collectively enhance EMS's efficiency and reliability, contributing to a more sustainable and resilient energy system.

For many grid-tied microgrids, there is a significant advantage to having weather and load forecasting methods integrated into the energy management system so that optimal grid-based charging and reliance on batteries can be maintained [96]. In islanded microgrids, however, a common practice is to use all available power to fully charge batteries and provide a diesel generator backup only when the battery state of charge has reached protection levels. However, this approach has several disadvantages as lithium ion batteries

Table 1 Summary of current AI methods used for sizing, fault detection, and energy management in a microgrid, with suggestions for how future research can be adapted for developing economies

Category	Current research	AI technology used	Suggestions for future research in developing economies
Sizing	• Managing uncertainties of renewable energy supply [77] • Multi-objective optimization of DER and forecasting [78]	• Software: HOMER and iHOGA [79] • AI algorithms: leveraging Genetic Algorithms (GA) [80], Harmony Search Algorithm (HSA) [81], Particle Swarm Optimization (PSO) [82], and Simulated Annealing (SA) [83]	• Growth-forward approach considering potential load increase • Multifactor optimization with a reliability consideration • Implementing algorithms that optimize operational costs and ease of maintenance
Fault Detection	• Improve accuracy of Identification, and characterization of power disturbances [84–86] • Fault Location Detection [87] • Smart anomaly information [85, 86]	• Type-2 Fuzzy Logic (FL) [88], Decision Tree [89], Artificial Neural Networks (ANN) [90, 91], Support Vector Machines (SVMs) [90, 91], K-Nearest Neighbors (KNN) [90], Naïve Bayes [90], Hybrid ANN-SVM models [91]	• Autonomous AI Systems • Local deployable algorithms • Super Resolution, energy data encoding • Exploring self-correction capabilities
Energy Management Systems	• Optimization of microgrid operations [14, 92] • Handling integration and variability of DER [93–95] • Load forecasting, weather forecasting, smart control [96, 97]	• Artificial Neural Networks [93], Fuzzy Logic Systems [94], Sliding Mode Controller [95] • Multi-agent systems [98], Game theory [17•], Markov decision processes [99]	• AI-based forecasting techniques for battery state-of-charge [97] • AI for operation of productive use of electricity • AI for creating and implementing electricity tariffs

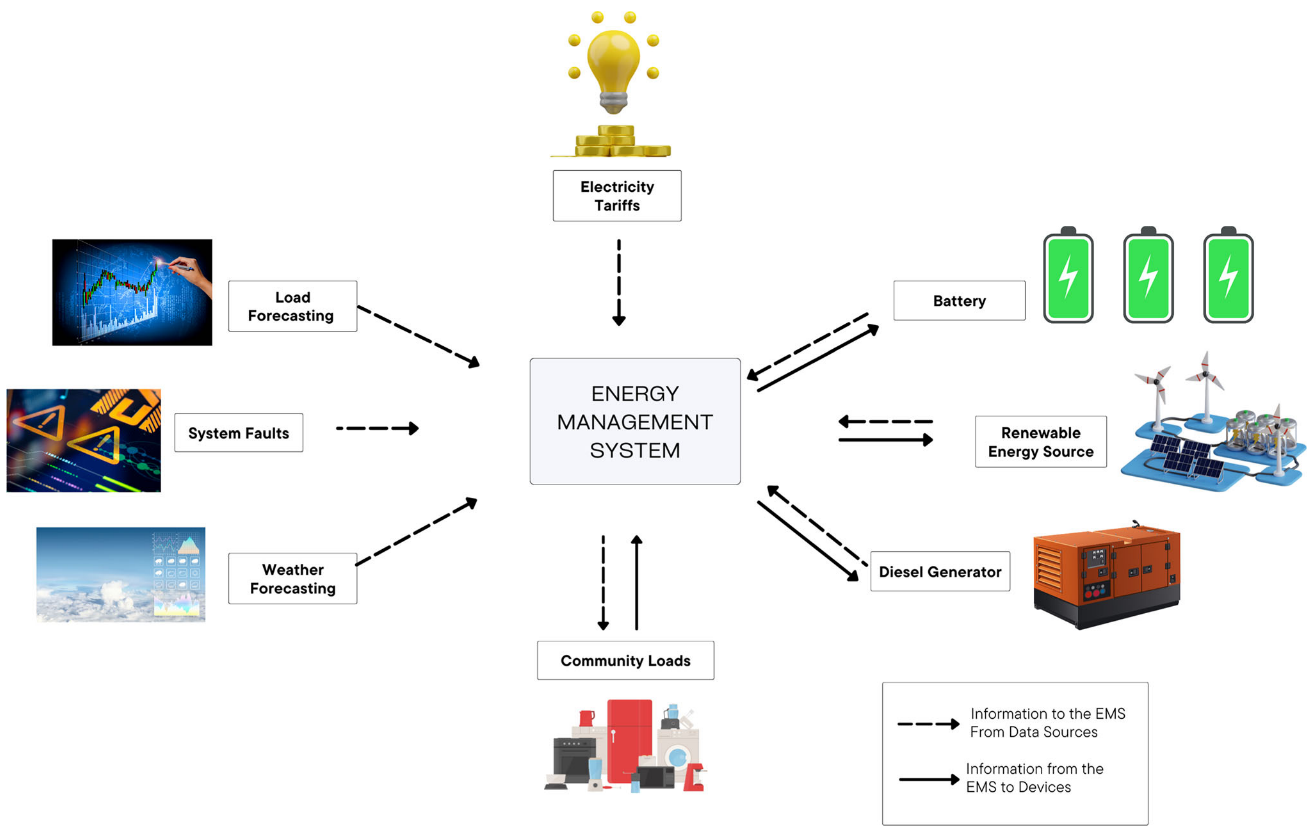

Fig. 4 An example of an EMS in a developing economy, with inputs for weather and load forecasting

have a high degree of self-degradation when kept at a high or low state of charge. Recent studies by Schulte et al. [97] found that the proposed operation strategy could reduce the average battery state-of-charge by 20% without causing power outages for the mini-grids in applied case studies on microgrids in Nigeria. This study used the statistical method autoregressive integrated moving average, of forecasting; however, there is great potential for AI-based future work in this area.

Fault Detection

Fault detection is the identification, segregation, and characterization of disturbances related to power quality within a power system [84]. In the context of a microgrid, fault detection strategies traditionally employ distributed sensors to monitor electricity parameters and identify anomalies that could indicate hazardous power conditions, potentially causing harm to the inhabitants or leading to equipment failure [85]. Traditional fault detection techniques largely depend on signal processing approaches such as Fourier transform, waveform transform, and eigenvalue analysis [87]. These methods are used to inform microgrid operators and, in some situations, operate autonomously to safeguard electrical equipment. Recent advancements in AI stand out as a promising solution, potentially offering superior detection capabilities for complex power disturbances and heightened accuracy in signal processing that may be overlooked by conventional methods [86].

A variety of AI-based mechanisms have been employed in the literature, including type-2 fuzzy logic [88], decision tree-induced fuzzy rule base intelligent protection schemes [89], support vector machines, and artificial neural networks [91]. Different machine learning techniques such as decision trees, K-nearest neighbors, support vector machines, and naïve Bayes have been used and compared for fault classification in microgrids as well [90]. Fuzzy logic and graph algorithms are another popular choice [102]. To control the autonomous switching of energy sources, many adaptive relays have been developed, including using a hybrid fuzzy-optimization method for optimal settings and coordination [103].

The protective considerations for rural microgrids differ vastly from those of urban or grid-tied microgrids. Rural microgrids are often constrained by factors such as a limited understanding of technological issues by the local community, economic limitations, a higher degree of exposure to severe environments, and an increased incidence of electricity theft [104]. Duly addressing these issues is crucial as they present additional complications that may not arise in larger microgrids. There is an opportunity for academic research to offer solutions for efficient identification and diagnosis of power quality problems, such as pinpointing the location and isolating the relevant components.

For a solution to be practically applicable in a microgrid environment, it should not require high-speed data transmission to a cloud-based system or should be locally deployable and deliver advanced power quality detection accuracy. Moreover, it should be accompanied by a comprehensive strategy for execution and integration of the fixing solutions and self-correction capabilities.

Sizing

Microgrid sizing is a crucial part of the microgrid implementation process, involving the selection of the energy generation capacity of one or many distributed energy resources (DER). A prominent challenge in standalone microgrid installation is sizing the generation components to reduce overall system cost while maintaining adequate electricity coverage through varying load conditions. While renewable energy sources are often considered an ideal solution, they provide additional challenges due to the uncertainty of renewable energy supply. In many rural communities, a photovoltaic system with battery storage and a diesel generator backup is often one of the simplest and most cost-effective methods of delivering zero or low-carbon emission during production [77].

Software solutions like HOMER and iHOGA have emerged as industry standards for microgrid sizing, accounting for weather forecasting and employing specific algorithms for optimization [79]. Alongside industry software solutions, there has been significant academic interest in developing various AI sizing algorithms focused on optimizing system cost and reliability [105]. These algorithms leverage artificial intelligence methods, including genetic algorithms [80], harmony search algorithm [81], particle swarm optimization [82], simulated annealing [83], and others [78, 80]. The defining feature of these AI-based sizing approaches is their ability to handle non-linear fluctuations of the microgrid components and the variable nature of the meteorological parameters. Some AI-based solutions have been designed with better accuracy and convergence and can ingress a wider range of operating parameters such as high-resolution time series data [106].

From an algorithm design perspective, it is imperative to consider not just the current energy requirements but also the potential future growth of the community energy demands, essentially creating a growth-forward approach [107]. One of the key challenges when looking at rural microgrid sizing is estimating energy growth over time among varying political and economic climates. In the context of developing economies, a more pragmatic approach might be to acknowledge the need for a reduced reliability factor in the short-term while devising a plan to increase electricity reliability over time—reducing the up-front cost of electrification [108].

In low- and middle-income countries, a reality for rural communities operating a microgrid is the often high costs for maintenance due to limited technical skillsets available locally. The economic barrier introduced by limited technical skills can be partially mitigated by implementing algorithms that reduce the operational cost of a microgrid in remote locations [107]. Furthermore, AI can be used to model future load growth and operational costs by using population growth forecasts and economic development indicators, which can support the scalability and future readiness of the system [109].

Future Artificial Intelligence Research

While significant research has focused on various technical AI-microgrid opportunities, there is also great potential for AI to address the various STEP challenges faced by developing economies. In this section, we break down the ways in which future research can be practically implemented into microgrids located in low- and middle-income countries.

Using AI to overcome *social challenges* presents an interesting perspective on electrification adoption opportunities. The recent advancements of large language models (LLM) have demonstrated their usefulness in enhancing education and explaining complex problems [110]. In cellular/ WI-FI enabled areas, an LLM can be used to support the adoption of electricity and electrical technology and explain use cases in the local language [111–113]. Alongside community adoption, AI can be leveraged to increase technical awareness and semantically search across energy components manuals and documents to help diagnose and resolve power quality issues by technicians [114].

Another key aspect in implementing energy solutions is navigating and overcoming the many *political challenges* facing communities. AI has shown much promise in fraud and anomaly detection—a useful feature for corruption identification [115]. Technology such as graph neural networks can be useful in identifying bad actors based on previous history, and their relation to other corrupt individuals [116, 117]. Additionally, machine learning algorithms, including decision trees, random forests, support vector machines, deep learning models like convolutional neural networks, recurrent neural networks, transformers, and anomaly detection algorithms, perform comprehensive data analyses—structured and unstructured—to discern and classify patterns indicative of suspicious activities [118, 119]. Natural language processing techniques and network analysis using graph theory provide in-depth insights into text data and complex relational data, respectively, further aiding the identification of potential corruption instances [120].

Economic challenges are often viewed as one of the most pronounced barriers to private sector involvement in electrification, which is important for widespread adoption. One of the biggest financial barriers facing microgrid developers is a lack of revenue from customers. To increase profitability, some microgrid operators have introduced productive use appliances to the community to increase revenues [121]. Upon implementation, community services such as commercial refrigeration, ice making, water purification, and other appliances can be introduced to provide additional revenue for a community. The scheduling and operation of these loads provide an interesting potential area for future AI research, as optimization and uncertainty are heavily involved. Finally, while some companies have set limits for the maximum electricity tariffs, by optimizing and understanding consumer load profiles, AI could help in the creation and implementation of better electricity tariffs, further increasing the payback of microgrids.

Overcoming the *technical challenges* associated with sizing, energy management, and fault detection in the context of constraints faced by developing economies requires a significant commitment. One key area of potential future study is developing methodologies for assessing the minimum level of sensing necessary for reliable, real-time grid state analysis. Likewise, due to the cost of data sensing and transmission, solutions such as localized algorithm deployments can optimize data processing while research on super-resolution data technologies can enhance operational efficiency and analysis of microgrids. Moreover, the development of economical yet efficient sensing solutions can reduce overall installation costs, a considerable benefit to developing economies with limited resources.

Conclusion

The integration of AI advancements into microgrids in low- and middle-income countries is a dynamic area of investigation requiring the concerted effort of various stakeholders. Microgrid installation companies often grapple with resource constraints, a lack of nuanced understanding of AI-based solutions, and issues related to data acquisition costs. Collaborations with academic researchers and a further emphasis on data-based approaches can guide these companies toward innovative, cost-effective solutions that support electrification effectively.

For both academics and industry, a systematic investigation of social-technical-economic-political (STEP) challenges prior to rural microgrid implementations would yield valuable insights. With community involvement and a proper STEP analysis, economically viable grid systems that seamlessly merge with the daily routines of community members can be implemented successfully. Alongside these efforts, there are great opportunities in AI models that can identify and help overcome the many challenges facing developing economies on the path to electrification today.

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Declarations

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